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Research Paper

Assessing urban landscape ecological risk through an adaptive cycle framework

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ABSTRACT

Cities are suffering various ecological risks due to rapid urbanization and global climate change. Urban landscape ecological risk assessment is conducive to identifying high risk areas and guiding risk prevention. However, few studies have characterized the dynamic processes of landscape ecological risk. In this study, taking Beijing City as a case study, the adaptive cycle in resilience theory was incorporated into a risk assessment framework using such three criteria as potential, connectedness, and resilience, together with integrating exposure and disturbance effects of risk sources. This framework contributed to understanding the complex interactions between landscapes and risk effects from a holistic and dynamic view. The results showed that the ecological risk of “potential” and “connectedness” weakened radially from downtowns to outer suburbs. The distributions of “resilience”, “exposure”, “disturbance”, and the final risk, all exhibited a concentric pattern of the higher risk, highest risk, and lowest risk sequentially from downtowns to outer suburbs. The results reflected the facts that residents living in downtowns had taken ecological restoration measures to reduce risk, while continuous urban constructions in outer suburbs increased the risk. In terms of the adaptive cycle phases of ecological risk, Yanqing, Miyun, Huairou, Mentougou, Fangshan and Pinggu districts were in the reorganization α-phase; Daxing, Changping, Shunyi and Tongzhou districts were in the exploitation r-phase; Dongcheng, Xicheng, Fengtai, Haidian, Chaoyang and Shijingshan districts were in the conservation K-phase. The results provided scientifically spatial guidance for implementing resilient urban planning, in order to realize sustainable development of metropolitan areas.

1. Introduction

Natural ecosystem is a significant basis for human survival and development. However, global climate change and rapid urbanization have exacerbated ecological risks and affected social sustainability (Estoque & Murayama, 2014). The U.S. Environmental Protection Agency defined ecological risk as the likelihood that adverse ecological effects would occur when an ecosystem and its components were exposed to multiple risk sources (USEPA, 1998). Ecological risk assessment is the prerequisite for risk control, and contributes to supporting environmental decision-making (Piet et al., 2017). In recent studies, ecological risk sources have extended from a single biochemical factor (Tarazona, 2013), to diverse sources caused by human activities and natural hazards (Van den Brink et al., 2016). In addition, risk receptors have also extended from ecosystems to systems coupling human and nature (Paukert, Pitts, Whittier, & Olden, 2011).

Urban ecological risks are characteristic of multi-source and multi-receptor influences with complex exposure and disturbance mechanisms. Most previous studies on urban ecological risk assessment discussed the effects of natural disasters such as geological changes (Carreño, Cardona, & Barbat, 2012) and flood hazards (Camarasa-Belmonte & Soriano-García, 2012). Given the complexity of urban ecological risks, the research trend of risk assessment is to characterize the spatial and temporal heterogeneity of risk sources and receptors, and risk effects in an interrelated perspective (Li, Kappas, & Li, 2017). The introduction of landscape ecology into the list of considerations follows this trend. Landscape ecological risk assessment (LERA) takes the landscape, the heterogeneous mosaics consisting of social and ecological systems, as the evaluation object. The traditional ecological risk assessment emphasizes on overlapping multiple risk sources to characterize risk patterns in a region, LERA focuses on spatializing the effects and responses of landscape to risk sources under the background

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of correlations among landscape patterns and ecological processes (Peng, Dang, Liu, Zong, & Hu, 2015).

At present, urban LERA is still in its infancy. Chinese scholars have put forward landscape ecological risk indices based on ecological vulnerability and disturbance indices (Mo, Wang, Zhang, & Zhuang, 2017). Such methods described the static pattern of ecological risk rather than the dynamic process of risk adaptation and interaction. However, if a region with low ecological risk exhibits an increasing trend of risk in the time series, it cannot be concluded the region is experiencing good environmental conditions. In this context, it is necessary to consider the city as a “living” adaptive system when applying LERA in urban environmental management.

The theory of resilience has emerged as a dynamic approach to analyzing how a system can deal with risks. Resilience is a concept originated from physics (Resnick & Taliaferro, 2011). Holling (1973) firstly introduced resilience in the field of ecology and defined it as the capacity of a system to absorb disturbance and remain essentially in the same state. Along with the introduction of socio-ecological systems (SESs), resilience theory is being perfected gradually (Adger, 2000). SESs are complex adaptive systems composed of human and nature, which have the major characteristics of historical dependency, nonlinearity, threshold effects, multiple stable states, self-organization, and limited predictability (Cumming et al., 2005). Resilience theory provides a more realistic viewpoint of enhancing the capacity of SESs to adapt to surprise and uncertainty (Lei, Wang, Yue, Zhou, & Yin, 2014).

The adaptive cycle is a key heuristic model within resilience theory and has been used to analyze the evolution of SESs (Burkhard, Fath, & Müller, 2011). The adaptive cycle describes such four sequential phases as exploitation (r), conservation (K), release (Ω), and reorganization (α) involving three changing features of potential, connectedness and resilience (Gotts, 2007). The feature of potential represents the accumulated capitals in systems, while for the feature of connectedness it encompasses the quantity and frequency of interactions among components (Grundmann, Ehlers, & Uckert, 2011). When affected by multiple risk sources, SESs resist and adapt to the risk effects in order to restore or maintain the stable states, which drive the evolution of the adaptive cycle (Walker, Gunderson, Kinzig, & Folke, 2006). The adaptive cycle has been applied to explore sustainable development of SESs under the background of global environmental change (Müller et al., 2015). With the maturity of resilience theory, the applications of adaptive cycle have mainly included two aspects. Firstly, a variety of case studies have explored the adaptability and transformability in complex systems such as agricultural systems (Rawluk & Curtis, 2016) and coastal zones (Angeler et al., 2015). Secondly, resilience theory has been applied to urban systems to develop a new concept, the resilient city, which has gradually penetrated into the theory and practice of urban planning and design since the 1990s (Meerow, Newell, & Stults, 2016). Furthermore, the concept of resilient city is integral to achieve the sustainable development of communities or cities (Sharifi, 2016).

Identification and assessment of landscape ecological risks are important for resilient city planning. Liu, Wang, Peng, Zhang, & Wei (2015) introduced a three-dimensional (3-D) adaptive cycle framework that integrated dynamic resilience factors into the risk assessment index system, which enriched the methodology of LERA. Nonetheless, their study did not further analyze the relationship between ecological risk and the adaptive cycle. In this study, urban adaptive cycle is thought to be driven by the interactions among ecological risk effects and urban landscape. When exposed to or disturbed by risk sources, urban landscape will respond in the change of landscape units, landscape structures and landscape processes, respectively corresponding to the interrelated features of potential, connectedness and resilience. Thus, a 3-D indicator system based on the “potential”, “connectedness” and “resilience” criteria can be developed for LERA focusing on the adaptive phases of landscape ecological risk.

Beijing City has become one of the most representative metropolitan areas with rapid urbanization in China. The contradictions between environmental protection and urban development are increasingly apparent. Natural disasters such as heat wave, soil erosion, waterlogging have seriously affected the health of urban residents and natural ecosystems. Thus, there is an urgent need for LERA to encourage the city to actively adaptive against ecological risks and look for new paths of urban development. Taking Beijing City as a case study area, this study is aimed to propose a 3-D indicator system for LERA, to identify the adaptive phases of urban landscape ecological risk, and to put forward spatial planning strategies of districts at different phases in the view of resilient city planning.

2. Materials and methods

2.1. Study area and data sources

Beijing City is located at the northern tip of the North China Plain, with a total area of 16,410 km^2. It is surrounded by Hebei Province except where it is adjacent to Tianjin City in the southeast. Beijing City comprises 16 administrative county-level subdivisions, including two downtowns (Dongcheng and Xicheng districts), four suburbs (Chaoyang, Haidian, Fengtai and Shijingshan districts), and ten outer suburbs (Changping, Fangshan, Mentougou, Shunyi, Tongzhou, Daxing, Yanqing, Huairou, Miyun and Pinggu districts). Approximately 38% of Beijing’s terrain is flat (in the east and south) and 62% is mountainous (in the north and west) (Fig. 1). Beijing City belongs to the warm temperate zone with the half-moist continental monsoon climate. The annual average temperature is approximately 10–12 °C and the annual precipitation is about 644 mm.

As the capital of China, Beijing City is the political, economic and cultural center of the country and has already developed into a typical metropolitan area. According to the statistical data for 2016, Beijing City had a total population of nearly 22 million and an urbanization rate of 86.5%. Along with the rapid socio-economic development, excessive population and industrial agglomeration, and uncontrolled spread of urban construction land have resulted in air pollution, soil erosion, soil pollution, urban heat island and other eco-environmental degradations in recent years. These problems seriously threaten regional ecological security and residential environmental quality in Beijing City.

In this study, the required data to calculate the indicators for LERA included remote sensing imagery, vegetation and terrain data, meteorological data and nighttime lights data. The data sources are listed in Table 1.

2.2. Conceptual framework

LERA takes the landscape as evaluation object. Landscape is regarded as the interrelated social and ecological system from a comprehensive and holistic view (Li, 2000). The effects of ecological risk may occur when landscapes are exposed to or disturbed by ecological risk sources, and the responses of SESs will trigger further changes in landscapes (Bauch, Sigdel, Pharaon, & Anand, 2016). These changes will show different characteristics in landscape patterns and processes at various spatial and temporal scales. The adaptive cycle, a heuristic model within resilience theory, provides a holistic and dynamic approach to understanding the complex interactions between landscapes and risk effects (Folke, Carpenter, Walker, & Scheffer, 2010; Ingalls & Stedman, 2016).

From a landscape perspective, the “adaptive” emphasizes on the capacity of adaptability, resilience, and transformability of the landscapes responding to risk effects (Walker, Holling, Carpenter, & Kinzig, 2004). The “cycle” articulates that landscapes can adapt against risk effects and move through the cyclic phases of exploitation (r), conservation (K), release (Ω) and reorganization (α), with changes in three interrelated features, i.e. potential, connectedness, and resilience (Bunce, Mee, Rodwell, & Gibb, 2009; Gotts, 2007; Gunderson &

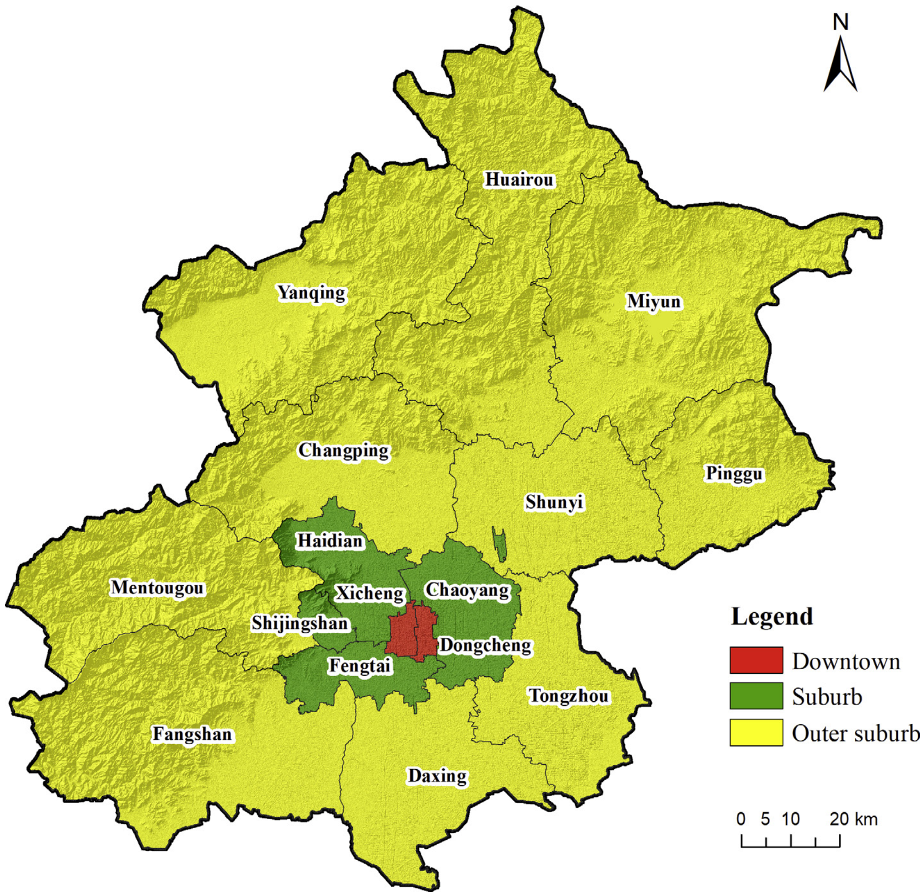

Fig. 1. Location of the study area.

Table 1
Data sources in the study.

Data	Source	Resolution
Landsat-8 satellite data (2014)	Geospatial Data Cloud (China) (http://www.gscloud.cn/)	30 m
Enhanced vegetation index (EVI) (2000–2014)	U.S. Government's 16-day L3 Global 250-m product (MOD13Q1) (https://modis.gsfc.nasa.gov/data/)	250 m
ASTER GDEM	Geospatial Data Cloud (China) (http://www.gscloud.cn/)	30 m
Monthly precipitation data (2014)	China Meteorological Data Sharing Service System (http://data.cma.cn/en)	Vector
DMSP-OLS nighttime lights (2000–2013)	National Geophysical Data Center at the U.S. National Oceanic and Atmospheric Administration (https://ngdc.noaa.gov/eog/dmsp.html)	1 km

Holling, 2002). In details, the potential feature represents the attributes of landscape units, and the connectedness feature describes the interconnections among landscape units characterized by landscape structures. Landscape units with different attributes and structures may have different responses to ecological risk sources, showing heterogeneous landscape patterns at the spatial scale. The resilience feature indicates the dynamic processes of landscape units. It evaluates the capacity of landscapes to recover from risk effects and can predict the possibilities of risk effects in the future at the temporal scale (Fig. 2). Resilience theory assumes that risks are ever present in SESs (Walker, Carpenter, Anderies, & Abel, 2002). The continuous interactions among human and nature, and risks and landscapes drive the dynamics of adaptive cycle (Chaffin & Gunderson, 2016; Cumming & Collier, 2005). In this respect, a 3-D framework consisting of "potential", "connectedness", and "resilience" criteria can be adopted to assess landscape ecological risk, respectively corresponding to the attribute of landscape unit, landscape structure, and landscape process.

The framework emphasizes on characterizing the reciprocal feedbacks between landscapes and ecological risks. It is hard to directly and comprehensively evaluate and spatialize multiple risk sources and receptors. However, risk effects and corresponding responses of landscapes are reflected in the changes of three features of landscapes, which can be evaluated by the 3-D criteria in this study. Thus, it is suitable to introduce the adaptive cycle to construct this framework to visualize the landscape ecological risk at the spatial and temporal scale.

As complex adaptive systems comprising human and nature, cities are considered typical SESs (Zhou, Pickett, & Cadenasso, 2017). Similar to the adaptive cycle of urban landscape, urban landscape ecological risk also shows phasic variation over time (Grundmann et al., 2011). In the exploitation (r) phase, continuous expansion of construction lands rapidly increases the potential of ecological risk, with the gradual decrease of ecological connectivity and resilience. After a long period of social progress and agglomeration, the potential of ecological risk generally arrives at a high level while ecological connectivity decreases at a low level. At this time, the city is tightly regulated and controlled by humans. The urban system becomes less flexible, more interconnected, and more vulnerable to internal or external disturbances because of the reduction of ecological resilience. This stage in the adaptive cycle is described as the conservation (K) phase. When disturbances exceed the ecological resilience threshold, the system may collapse suddenly and the accumulated capitals release rapidly. Thereafter, ecological connectivity and ecological resilience begin to gradually increase; this is the release (Ω) phase. In the subsequent reorganization (α) phase, the potential of ecological risk may reach its lowest value and ecological connectivity and resilience are at their

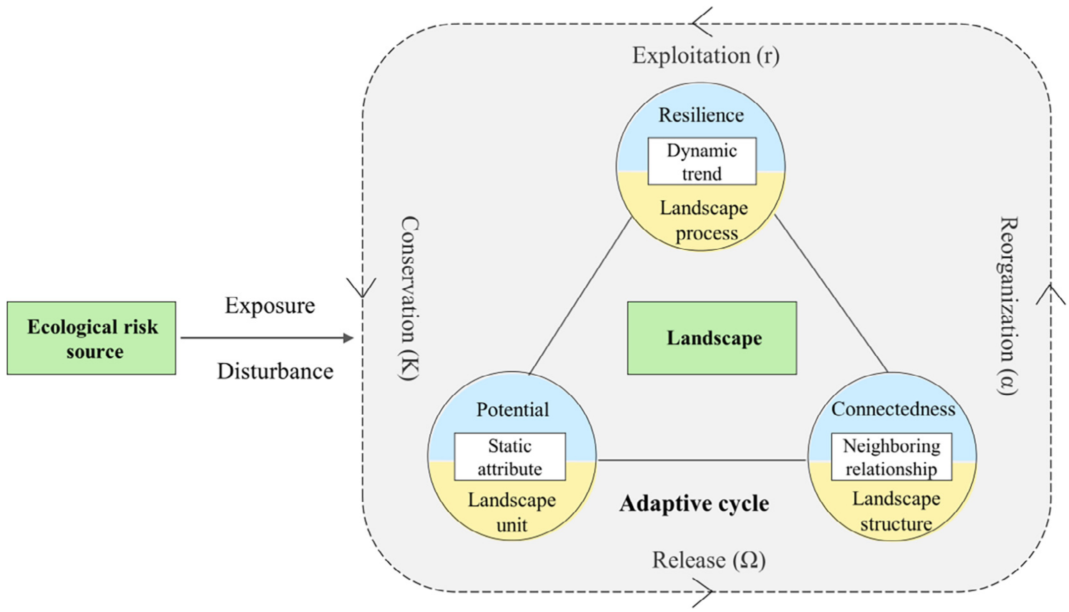

Fig. 2. Conceptual framework for urban landscape ecological risk assessment.

highest values. The greatest uncertainty and opportunity for innovation exists in this phase, and a new adaptive cycle may proceed from this phase (Olsson, Gunderson, Carpenter, & Ryan, 2006).

2.3. Indicator system

The rapid development of society and economy has caused a series of landscape ecological risks in Beijing City. On the one hand, urban sprawl constantly transforms ecological land into impervious surface, leading to the decline and fragmentation of ecological patches. It is the main factor causing the landscape ecological risks of Beijing City (Xie, Huang, He, & Zhao, 2018), which embodies in the change of biomass, landscape diversity, landscape connectivity, etc. On the other hand, the region has suffered from natural disasters such as heat wave (Wang & Gong, 2010), soil erosion (Bai et al., 2012), and landslide and debris flow (Cheng, Wang, Zhao, & Zhao, 2016), which has led to severe risks effects. Focusing on these issues, twelve relevant indicators were selected to characterize the landscape ecological risks. Besides, it is necessary to distinguish between exposure and disturbance effects of the risk sources in LERA (USEPA, 1998). "Exposure" indicates that as long as landscape exposed to the risk sources it may result in risk effects, which is related to the biophysical attributes of landscape. "Disturbance" refers to that only landscape disturbed by the risk sources can cause risk effects, which is related to the processes of human interference and climate change. It helps to understand the effects of the risk sources on the risk receptors, and provides more effective way to prevent landscape ecological risk.

2.3.1. Indicators for "potential" criterion

"Potential" criterion represents the effects and responses of static attributes of landscape units to ecological risk sources. The indicators evaluate the potential of the heterogeneous landscape units for ecological risk, with the increase of the value suggesting the increase of the risk potential (Table 2).

Slope indicator measures the potential of the geologic risk due to terrain characteristics. The soil loss, landslide and debris flow increase with land slope (Donjadee & Tingsanchali, 2013), and adversely affect the SESs. China's sloping land conversion program proposed that cropland with the slope over 25° should be converted to forest land. Accordingly, 25° was set as a risk threshold, which meant a slope exceeding 25° was assigned the highest risk of 1. Another threshold was set to be 2° (Liu, Peng, Zhang, & Zhao, 2015), with a slope less than 2° assigned the lowest risk of 0.

Land use and land cover indicator evaluates the potential of the ecological risk of the heterogeneous landscape patches. Each land use type was assigned a specific value. As the construction land has the most significant and negative interaction between SES and ecological risk, it was assigned the value of 1, and conversely, 0 was assigned to the forest land.

Vegetation coverage indicator reflects the potential of the ecological risk in view of the health of natural ecosystem. Vegetation plays an essential role in maintaining ecosystem services and decreasing ecological risks. The enhanced vegetation index (EVI) has been developed to improve the quality of vegetation monitoring in high biomass vegetated areas (Jiang, Huete, Didan, & Miura, 2008), and thus it was used to measure the vegetation coverage.

Land surface brightness temperature indicator represents the heat-related risks of urban heat island and heat waves. Worsened by climate change and rapid urbanization, the risks have negative impact on the ecosystems and urban populations (Chow, Brennan, & Brazel, 2012). The higher the temperature, the severer the ecological risk.

Rainfall erosivity is an effective indicator for assessing soil erosion risk, considering rainfall intensity and amount. The index can be calculated based on Wischmeier's empirical formula (Wischmeier, Johnson, & Cross, 1971), using average monthly rainfall data.

Nighttime light intensity can indirectly reflect the intensity of human activities (Jing, Yang, Yue, & Zhao, 2015). In general, the regions with high value mean the high-density urban agglomeration and the significant human-induced force on natural ecosystems (Ma, Zhou, Pei, Haynie, & Fan, 2012). The normalized DN value of the stable lights data from file F182013 was used in this study.

2.3.2. Indicators for "connectedness" criterion

"Connectedness" criterion represents the effects and responses of spatial structures of landscape units to ecological risk sources. The indicators assess the possibility of different landscape structures for ecological risk, with the increase of the value standing for the increase of risk possibility (Table 2).

Shannon's diversity index (SHDI) indicates the diversity of landscape types. The richer (more diverse) landscape types in a given region, the stronger the interactions among neighboring landscape units, and the lower the chances of system collapse under risk effects. SHDI was

Table 2
Indicator system for urban landscape ecological risk assessment.

Criteria (weights)	Effects of risk sources	Indicators (weights)	Normalization method
Potential (0.493)	Exposure	Slope (0.114)	Positively normalized from 2° to 25°
		Land use and land cover (0.032)	Construction land, unused land, farmland, grassland, water body, and forest land was set as 1, 0.9, 0.5, 0.2, 0.1, and 0, respectively
		Vegetation coverage (0.127)	EVI $<$ 0.1 was assigned as 1 with EVI $>$ 0.8 for 0. Negatively normalized for EVI from 0.1 to 0.8
	Disturbance	Brightness temperature (0.041)	Positively normalized from 0 to 1
		Rainfall erosivity (0.019)	Positively normalized from 0 to 1
		Nighttime light intensity (0.160)	Positively normalized from 0 to 1
Connectedness (0.311)	Exposure	Shannon's diversity index (0.050)	Negatively normalized from 0 to 1
		Integral index of connectivity (0.145)	Construction land was assigned 1 and other land use types were assigned with the value of 1 – IIC
	Disturbance	Distance to construction land (0.086)	Negatively normalized from 0 to 1
		Road network density (0.030)	Positively normalized from 0 to 1
Resilience (0.196)	Exposure	Vegetation coverage trends (0.131)	If the indicator presented an increasing trend (slope ≥ 0), the value was negatively normalized from 0 to 0.5; if slope $<$ 0, the absolute value of the indicator was positively normalized from 0.5 to 1
	Disturbance	Nighttime light intensity trends (0.065)	Positively normalized from 0 to 1

calculated using the moving window technique in FRAGSTATS 4.2 software (http://www.umass.edu/landeco/research/fragstats/fragstats.html) with the movement radius set to 300 m.

The integral index of connectivity (IIC) measures the extent to which the landscape patches promote or hinder the movement of ecological processes. Habitat patches with good connectivity play significant roles in achieving the integrated ecological functions and ecosystem services. A larger IIC value means better landscape connectivity, less patch fragmentation and lower ecological risk (Saura and Torné, 2009). The IIC value was quantified using Conefor Sensinode 2.6 software (http://www.conefor.org/).

The distance to construction land indicator characterizes the disturbance of urban expansion to the surrounding ecological lands. The closer the area is to construction land, the higher the possibility of being disturbed by human activities. This indicator was calculated by the Euclidean distance tool using ArcGIS 10.2 software.

Road network density represents the disturbance of road construction to ecological land connectivity. The ecological risk increases as the density of the road network increases (Mo et al., 2017). Kernel density estimation was applied to calculate this indicator using road network data of Beijing City.

2.3.3. Indicators for "resilience" criterion

"Resilience" criterion represents the effects and responses of the dynamic processes of landscape units to ecological risk sources. The indicators evaluate the capacity of the adaptability and resilience of landscape units for ecological risk. The higher value reflects the greater possibility for ecological risk in the future.

Vegetation coverage trends indicator measures the ecological resilience and sustainability in a region. An increasing trend suggests the high resilience and strong sustainability of natural ecosystem, and accordingly, the anticipated ecological risk is likely to decrease. A series of multi-temporal EVI images from 2000 to 2013 were obtained using the maximum value composite procedure. The vegetation coverage trend was analyzed by the slope of linear regression pixel-by-pixel.

Nighttime light intensity trends indicator reflects the disturbance of human activities on natural ecosystem. A significant increasing trend indicates a strong intensity of disturbance with high ecological risk, and vice versa. Linear trend analysis was employed to describe the trend of nighttime light intensity from 2000 to 2013. Due to the rapid development of Beijing City in recent years, the intensity of nighttime light was continually increasing during this period, and the slope of the trend was always positive.

Generally speaking, each raster layer of indicators for LERA was handled positively and normalized to values between 0 and 1, as detailed in Table 2. The weights of the indicators were scored using the AHP method (Shiau & Liu, 2013). Among them, the risk effects of human and vegetation activities were regarded as the most significant impact factors on urban SESs, and thus the indicators related to nighttime light intensity and vegetation coverage were given larger weights.

3. Results

3.1. Spatial distribution of urban landscape ecological risk indicators

Fig. 3 showed spatial patterns of the 12 indicators, representing the interactions among urban landscape and ecological risks. Firstly, risk intensity of most indicators weakened from the downtowns to the outer suburbs, including those for land use and land cover, vegetation coverage, brightness temperature, nighttime light intensity, distance to construction land, IIC, and road network density. High-risk areas were distributed mainly in the southeastern plains of Beijing City and low-risk areas were mostly located in the mountainous areas. These distribution patterns were closely related to the urban sprawl of Beijing City in recent years. The original ecological lands were replaced by the impervious surfaces that resulted in significant reductions of vegetation coverage, accompanied by rising surface temperature. Moreover, the density of road network and the intensity of nighttime light increased, with the decreasing of the connectivity of ecological lands.

Secondly, the distributions of SHDI and slope indicators were different from the above indicators, which were basically determined by the types and attributes of the landscape units. For the SHDI indicator, high-risk regions were the mountainous areas with high terrain, while land cover in these areas was mostly a single type of forest land. Low-risk areas in the southeastern plains had various types of land cover. The distribution of the rainfall erosivity indicator showed that the lowest risk was in the mountainous areas and the risk gradually increased towards the eastern plains. The distributions of indicators embodied the complexity and comprehensiveness of urban landscape

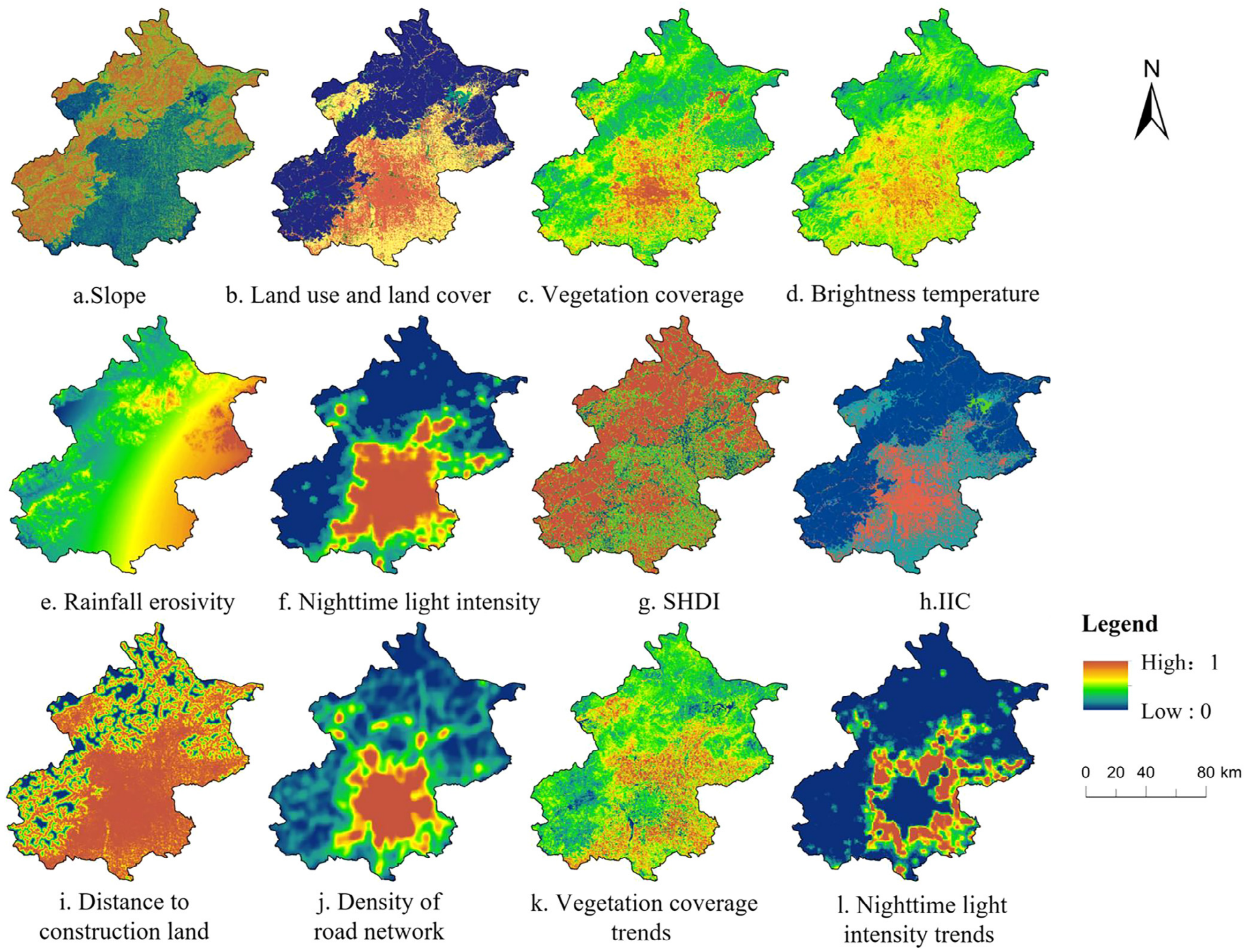

Fig. 3. Spatial patterns of urban landscape ecological risk assessment indicators in Beijing City (SHDI = Shannon's Diversity Index, IIC = Integral Index of Connectivity).

ecological risks.

Thirdly, spatial patterns of vegetation coverage trends and nighttime light intensity trends were similar, basically conforming to the three concentric circles where the risk varied sequentially from low to high and back to low, along with the increasing distance from the downtowns to the outer suburbs. Specifically, the downtowns and suburbs had the lowest risk, while the plains of outer suburbs had the highest risk. For the nighttime light intensity trends indicator, the value was 0 in the downtowns because the indicator had reached the highest since the year 2000, indicating the persistent high risk in these areas. It was worth noting that the risk in Tongzhou, Shunyi, Daxing, and Changping was increasing significantly. These areas were important regions for urban construction of Beijing City. For the vegetation coverage trends indicator, the low ecological risk in the downtowns and suburbs showed that highly developed areas had high ecological resilience and the risk could be controlled. In addition, the risk in the west of Fangshan and Mentougou, and in the north of Yanqing, Huairou, Miyun and Pinggu was also low. The land use type in these areas was predominantly forest land, and the low risk may due to the Grain for Green Program implemented in recent years. However, the highest ecological risk areas were also located in the plains of outer suburbs.

3.2. Spatial pattern of urban landscape ecological risk

The indicators were weighted and overlaid to map the spatial patterns of ecological risk in terms of criteria for "potential", "connectedness", and "resilience", and exposure and disturbance (Fig. 4). Then, all the indicators were integrated to obtain the final landscape ecological risk map for Beijing City at the pixel level. Firstly, "potential" and" connectedness" criteria characterized spatial heterogeneity of current ecological risk. They were determined by the distribution patterns of most indicators such that ecological risk decreased from the downtowns to the outer suburbs. Secondly, risk of disturbance was distinctly higher than that of exposure and expanded more widely to the outer suburbs. These patterns implied that external disturbances such as human activities had greater impacts on the health of urban systems than do other factors. Thirdly, the "resilience" criterion showed that the ecological risk was low in the downtowns and suburbs, which meant cities still had ecological resilience under high exposure and disturbance risk. That is to say, a risk assessment system that considers only the "potential" and "connectedness" criteria would lead to erroneous results, as it ignores the capacity of adaptability of the system itself and the positive influence of human regulation. In short, inconsistency within each criterion layer also reflects the complexity and diversification of urban LERA. The integration of these layers to the final map may weaken or strengthen some indicators due to the subjectivity of the weights. However, multiple risk criteria will provide a more comprehensive reference for the LERA than does reliance on a single criterion.

The final (i.e., integrated) landscape ecological risk map (Fig. 4f) showed that the areas of the highest risk were distributed mainly in the plain of outer suburbs with a circular pattern. All were vigorously

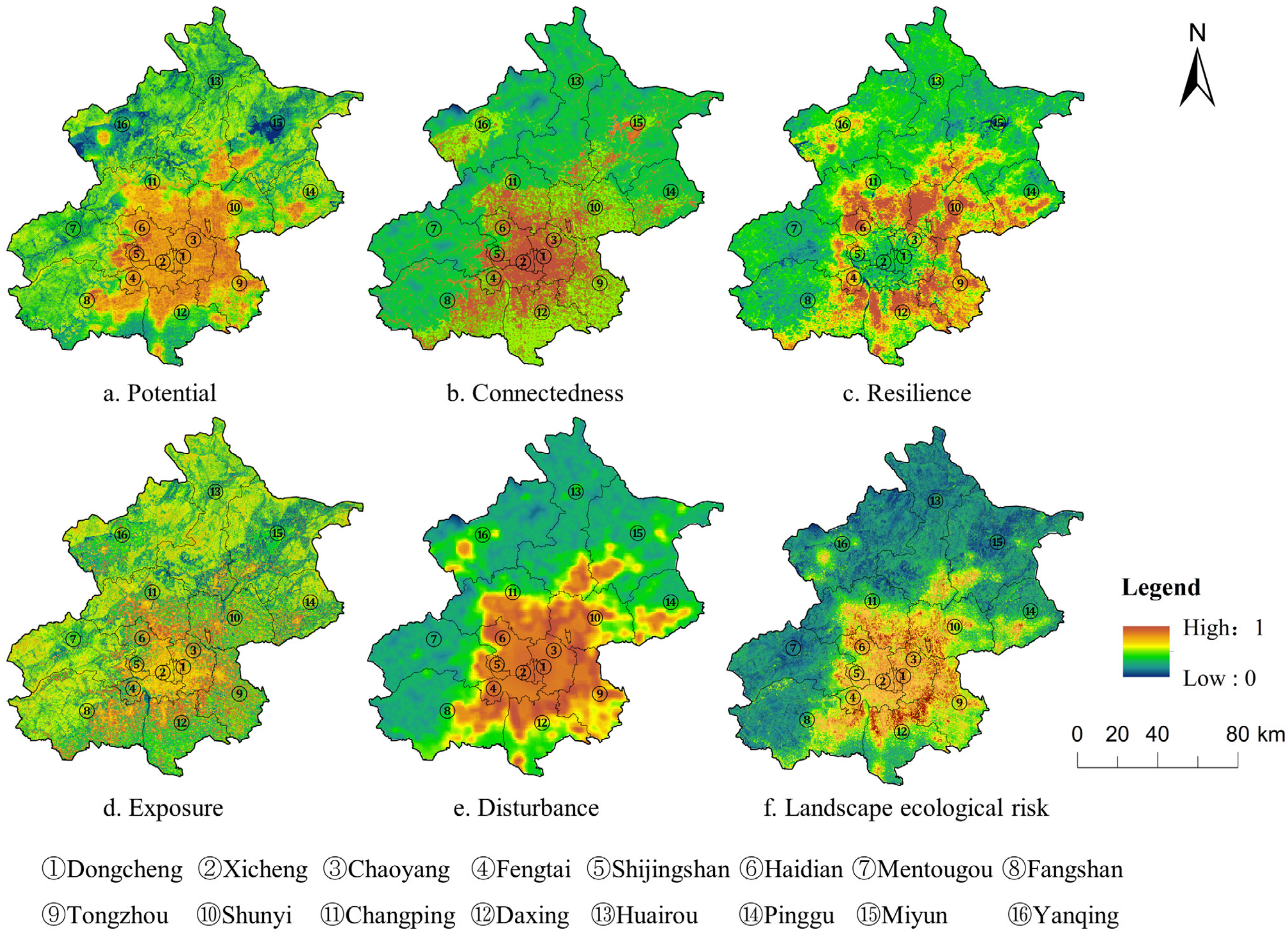

Fig. 4. Spatial patterns of urban landscape ecological risk in Beijing City.

developing areas in Beijing City currently. Furthermore, areas with relatively high ecological risk were in the downtowns and suburbs, indicating that people had taken effective measures to protect natural ecosystem even though economic development had reached high levels in these areas. These results proved that various risk control measures taken in Beijing City (such as green infrastructure construction and eco-environmental governance) had contributed to reducing the ecological risks. Areas with relatively low ecological risk were distributed at the fringes of suburbs. The land cover in these areas was mostly farmland, for which the ecological risk was generally higher than that for natural ecosystems. Finally, the areas with the lowest ecological risk were located in northern and western mountainous areas of Beijing City, with most of forest coverage.

3.3. Adaptive cycle phase of urban landscape ecological risk

Ecological risks interact with urban landscapes and exist in each phase of urban adaptive cycle. Similarly, characteristics of ecological risk can also be described in the adaptive cycle phases. In this study, the average risk value of 3-D criteria layer of each district in Beijing City was calculated, and then the zero-mean normalization method was used to standardize the average values of districts for each criterion. The risk values varied in different districts, corresponding to different characteristics of ecological risk at the district level. As shown in Fig. 5, all the districts could be divided into three categories based on the similarity of risk characteristics. In details, the districts of Yanqing, Miyun, Huairou, Mentougou, Fangshan and Pinggu had the lowest risk values for each layer. The districts of Daxing, Changping, Shunyi and Tongzhou had lower values for "potential" and "connectedness" layers and the highest value for "resilience" layer. The districts of Fengtai, Xicheng, Dongcheng, Haidian, Chaoyang and Shijingshan had the highest risk values of "potential" and "connectedness" layers, but a lower value for "resilience" layer.

With the combination of spatial patterns of landscape ecological risks, the adaptive cycle phases of urban landscape ecological risk could be divided at the temporal scale. The risk values of all the districts were plotted in a three-dimensional coordinate system with "potential", "connectedness" and "resilience" as the axes. The adaptive cycle model was also overlaid to produce a schematic diagram of the ecological risk phases of the districts in Beijing City (Fig. 6). Table 3 summarized the characteristics of 3-D risk value at each phase illustrated in Fig. 6.

As shown in Fig. 6, in the exploitation (r) phase of urban landscape ecological risk, all the risk values of "potential", "connectedness" and "resilience" displayed an increasing trend from low to high. The districts of Daxing, Changping, Shunyi and Tongzhou were in this phase, which occupied the pixels with the highest landscape ecological risk in Beijing City. The regions were significantly affected by the rapid urbanization process with the tranformation from ecological lands to construction lands, which resulted in the increase of risk potential, the decrease of ecological connectedness and the sharp decline in ecological resilience.

In the conservation (K) phase of urban landscape ecological risk, the risk values of "potential" and "connectedness" reached the highest, while the high risk value of "resilience" showed a decreasing trend. The districts of Xicheng, Dongcheng, Fengtai, Chaoyang, Shijingshan and Haidian were in this phase, which contained the pixels with higher landscape ecological risk in Beijing City. These districts were highly urbanized areas and had developed to a mature and stable stage.

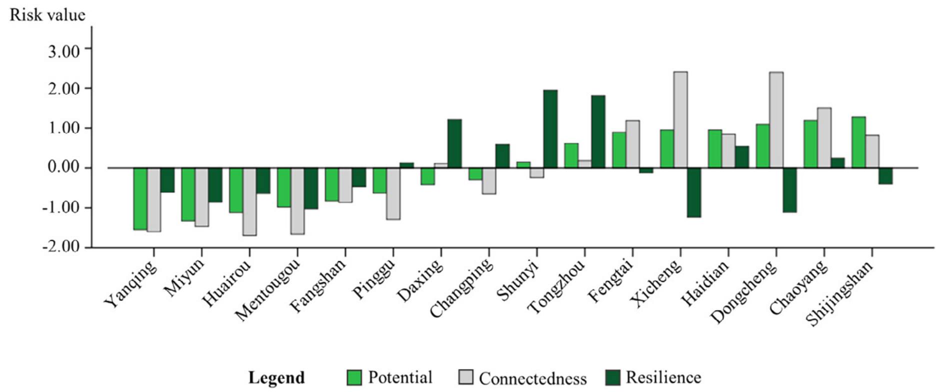

Fig. 5. 3-D values of landscape ecological risk of each district in Beijing City.

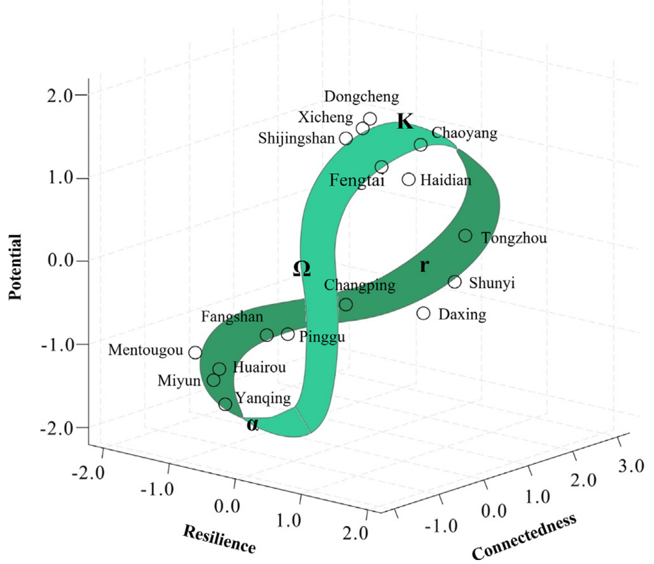

Fig. 6. Adaptive cycle phase of urban landscape ecological risk of each district in Beijing City.

Table 3
Characteristic description of the 3-D risk value in adaptive cycle phases.

Risk phase	Representative region	Potential layer	Connectedness layer	Resilience layer
Exploitation, r	Urban developing area	From low to high	From low to high	From low to high
Conservation, K	Urban central area	High	High	High
Release, Ω	Collapsed area	From high to low	From high to low	From high to low
Reorganization, α	Undeveloped area	Low	Low	Low

Although the risk potential was high and ecological connectivity was low, the ecological resilience represented an increasing trend due to human protections on the natural ecosystems.

In the release (Ω) phase of urban landscape ecological risk, the risk values of "potential", "connectedness" and "resilience" showed a decreasing trend from high to low. When a city encounters strong disturbances that exceed the resilience threshold, accumulated social capitals and ecological connectivity will be severely damaged in a short time. In this study, Beijing City was in the stage of rapid development, and thus the release phase had not yet occurred.

In the reorganization (α) phase of urban landscape ecological risk, the risk values of "potential", "connectedness" and "resilience" were low. The districts of Yanqing, Miyun, Huairou, Mentougou, Fangshan and Pinggu were in this phase, which had the pixels with the lowest landscape ecological risk in Beijing City. With low human interferences, landscape ecological risks in these areas mainly related to the biophysical landscape attributes such as terrain and biomass.

4. Discussion

4.1. Challenges in adopting adaptive cycle in LERA

Adopting the adaptive cycle in LERA has raised challenges in two aspects, i.e. theoretical integration and methodological application. Firstly, the challenge lies in how to integrate adaptive cycle with LERA to discuss the adaptive phases of landscape ecological risk and corresponding characteristics in each phase. In general, LERA can quantitatively evaluate the heterogeneity of ecological risk in spatial dimension to predict the possibility of risk. However, adaptive cycle qualitatively describes the cyclic process of ecological risk in temporal dimension and depicts the attributes of four phases. In this study, it was aimed to extend risk prediction to risk phase's identification, building a bridge between LERA (spatial dimension) and the adaptive cycle (temporal dimension).

Given that the complete processes of adaptive cycle do not always exist in the development of cities, or all the phases cannot be captured by limited data, the paradigm of "trading space for time" (Singh, Werkhoven, & Wagener, 2014) was used effectively in this study. The adaptive phases of landscape ecological risk over time were discussed through contrasting the spatial characteristics of risk at the district level. Due to the different properties of SESs, each district changed at different rate responding to the risk effects in the same study period. Accordingly, the 3-D attributes of landscape ecological risk of the districts can be treated as the attributes of each phase in temporal scale.

Secondly, the challenge lies in how to apply the three abstract features of adaptive cycle to concretely construct the 3-D indicator system of LERA. The adaptive cycle is considered as a conceptual model in previous studies, and there remains a relative paucity of quantitatively analyzing the potential, connectedness and resilience features (Grundmann et al., 2011). In this study, it was aimed to spatialize the features to apply to the landscape ecological risk studies. In details, potential stands for the "wealth" of the SESs (Holling, 2001), in the form of social and ecological capitals varying in spatial units, quantified by the pixel values of the raster images. Connectedness refers to the tightness of associations among landscape units, measured by the spatial analysis of neighborhood relationships. Resilience measures the capacity of the landscape to cope with risks, which has been an important attribute in describing landscape dynamics (Burkhard et al., 2011), quantified by the trend analysis in time series. Therefore, spatial indicators can be adopted for characterizing attributes of landscape unit, landscape structure and landscape process, to measure the effects of landscape ecological risk.

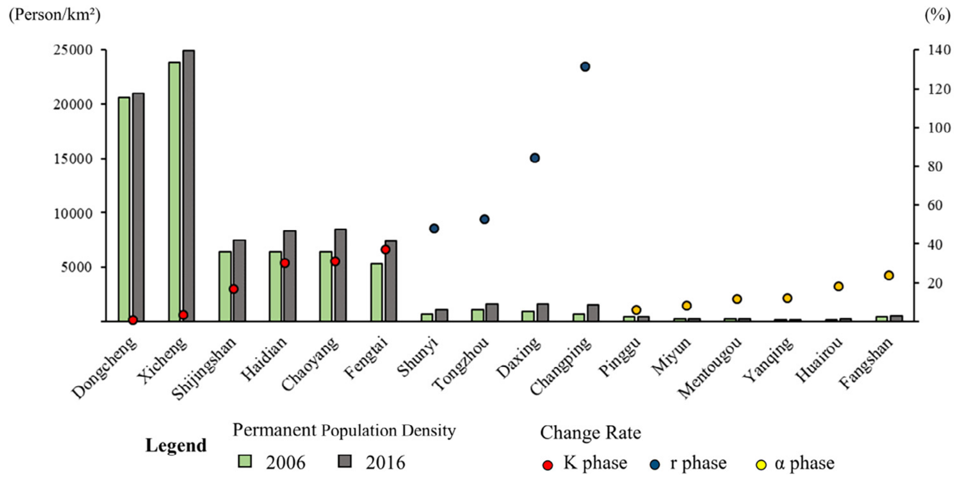

Fig. 7. Permanent population density of each district in Beijing City and the change rate during 2006–2016.

4.2. Implications for urban planning and landscape management

This study provides a valuable framework for LERA and supports the practice of spatial planning and landscape management of cities. Firstly, adaptive cycle was combined to decompose the assessment indicator system in a hierarchical way. It suggested that landscape ecological risk management and prevention should be implemented not only on the local landscape units, but also on the overall landscape structures in spatial scale, while considering landscape processes in temporal scale. Moreover, discussing the exposure and disturbance effects of risk sources could help to distinguish the emphasis of risk control on adapting human interference and climate change, or changing the biophysical conditions of landscape.

Secondly, what should be emphasized was that landscape ecological risk could not be avoided and eliminated in the development of cities (Davoudi, Shaw, & Haider, 2012). A profound shift is necessary for urban planners to address ecological risk management from "command and control" to "learn and adapt" with an anticipative and flexible attitude (Teigão dos Santos & Partidário, 2011). With the combination of the functional zones of Beijing City according to the administrative divisions in 2016, and the Permanent Population Density data (Fig. 7) from *The Beijing Regional Statistical Yearbook 2007* and *2017*, spatial planning strategies for districts of Beijing City in different adaptive phases could be put forward.

Daxing, Changping, Shunyi and Tongzhou districts were in the exploitation (r) phase, which lied in the new urban development zone. These regions had relatively low population density but extremely high rates of population growth. In these regions, ecological lands kept transforming to the impervious surfaces. Urban planners should focus on effectively restricting the sprawl of construction lands to decrease the potential of ecological risk. Protecting the critical and concentrated contiguous ecological patches by building forest parks and city parks could be an effective approach to maintaining the connectivity and resilience of natural ecosystems (Su et al., 2016).

Dongcheng, Xicheng, Fengtai, Haidian, Chaoyang and Shijingshan districts were in the conservation (K) phase, which lied in the core functional zone and the urban function extended zone. These districts had basically reached the full urbanization with the highest population density and higher growth rates. Therefore, the potential of the ecological risk could not be significantly reduced. Urban planners should focus on optimizing landscape patterns. Increasing small-scale but vital ecological patches and constructing crucial ecological corridors both could improve the connectivity and integrity of natural ecosystems. In addition, exploring various forms of urban green space construction such as community garden, green roof, etc., might also improve the resilience of SESs (Meerow & Newell, 2017).

Yanqing, Miyun, Huairou, Mentougou, Pinggu and Fangshan districts were in the reorganization (α) phase, which lied in the new urban development zone and the ecological conservation zone. Population density in these areas was very low with the lowest growth rate. These areas were highly covered with natural ecosystems and regarded as the important ecological barriers of Beijing City. Urban planners should focus on controlling and reducing intensified disturbance risks from human activities to keep the capacity of resilience of natural ecosystems.

In the release (Ω) phase, the regions would undergo serious disturbances that eventually led to collapse. Urban planners should focus on adapting against risk and finding opportunities for urban innovation and transformation. It was necessary to optimize the unreasonable landscape patterns in order to improve the resilience of the SESs, allowing the city to evolve to the next round of the adaptive cycle (Ahern, 2011; Porter & Davoudi, 2012). The ultimate goal was to meet the realistic needs of resilient urban planning and provide a more scientific guidance for the sustainable development of urban landscape.

5. Conclusions

Ecological risks due to natural disasters and human activities have caused adverse effects on urban landscape. Although there are various case studies on urban LERA, few are conducted to combine the static spatial patterns with dynamic temporal processes of risk effects. In this study, adaptive cycle was introduced to build a 3-D LERA framework comprised of three key criteria, i.e. "potential", "connectedness" and "resilience", integrating the effects of risk sources of exposure and disturbance with a case study in Beijing City. The results showed that most indicators of the "potential" and "connectedness" criteria weakened spatially from the downtown to the surrounding outer suburbs. Furthermore, the distributions of "resilience", "exposure", "disturbance", and risk layers all exhibited a pattern of three concentric circular areas comprising higher risk, highest risk and lowest risk sequentially from the downtown to the outer suburbs. These spatial patterns indicated that human regulation of ecological restoration could reduce ecological risks to some degree, which had a positive meaning for the management and control of urban ecological risks. In addition, the adaptive cycle of urban landscape ecological risk was divided into four phases, and spatial planning strategies for each phase were proposed from the perspective of resilient urban planning.

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References

Adger, W. N. (2000). Social and ecological resilience: Are they related? *Progress in Human Geography, 24*(3), 347–364.

Ahern, J. (2011). From fail-safe to safe-to-fail: Sustainability and resilience in the new urban world. *Landscape and Urban Planning, 100*(4), 341–343.

Angeler, D. G., Allen, C. R., Garmestani, A. S., Gunderson, L. H., Hjerne, O., & Winder, M. (2015). Quantifying the adaptive cycle. *PLoS One, 10*(12), e0146053.

Bai, Y., Ouyang, Z., Zheng, H., Li, X., Zhuang, C., & Jiang, B. (2012). Modeling soil conservation, water conservation and their tradeoffs: A case study in Beijing. *Journal of Environmental Sciences, 24*(3), 419–426.

Bauch, C. T., Sigdel, R., Pharaon, J., & Anand, M. (2016). Early warning signals of regime shifts in coupled human-environment systems. *Proceedings of the National Academy of Sciences of the United States of America, 113*(51), 14560.

Bunce, M., Mee, L., Rodwell, L. D., & Gibb, R. (2009). Collapse and recovery in a remote small island – A tale of adaptive cycles or downward spirals? *Global Environmental Change, 19*(2), 213–226.

Burkhard, B., Fath, B. D., & Müller, F. (2011). Adapting the adaptive cycle: Hypotheses on the development of ecosystem properties and services. *Ecological Modelling, 222*(16), 2878–2890.

Camarasa-Belmonte, A. M., & Soriano-García, J. (2012). Flood risk assessment and mapping in peri-urban Mediterranean environments using hydrogeomorphology. Application to ephemeral streams in the Valencia region (eastern Spain). *Landscape & Urban Planning, 104*(2), 189–200.

Carreño, M. L., Cardona, O. D., & Barbat, A. H. (2012). New methodology for urban seismic risk assessment from a holistic perspective. *Bulletin of Earthquake Engineering, 10*(2), 547–565.

Chaffin, B. C., & Gunderson, L. H. (2016). Emergence, institutionalization and renewal: Rhythms of adaptive governance in complex social-ecological systems. *Journal of Environmental Management, 165*, 81–87.

Cheng, W., Wang, N., Zhao, M., & Zhao, S. (2016). Relative tectonics and debris flow hazards in the Beijing mountain area from DEM-derived geomorphic indices and drainage analysis. *Geomorphology, 257*, 134–142.

Chow, W. T. L., Brennan, D., & Brazel, A. J. (2012). Urban heat Island research in Phoenix, Arizona: Theoretical contributions and policy applications. *Bulletin of the American Meteorological Society, 93*(4), 517–530.

Cumming, G. S., Barnes, G., Perz, S., Schmink, M., Sieving, K. E., Southworth, J., et al. (2005). An exploratory framework for the empirical measurement of resilience. *Ecosystems, 8*(8), 975–987.

Cumming, G. S., & Collier, J. (2005). Change and identity in complex systems. *Ecology & Society, 10*(1), 585–607.

Davoudi, S., Shaw, K., & Haider, L. J. (2012). Resilience: A bridging concept or a dead end? *Planning Theory & Practice, 13*(2), 299–333.

Donjadee, S., & Tingsanchali, T. (2013). Reduction of runoff and soil loss over steep slopes by using vetiver hedgerow systems. *Paddy & Water Environment, 11*(1–4), 573–581.

Estoque, R. C., & Murayama, Y. (2014). Measuring sustainability based upon various perspectives: A case study of a hill station in southeast Asia. *Ambio, 43*(7), 943–956.

Folke, C., Carpenter, S. R., Walker, B., & Scheffer, M. (2010). Resilience thinking: Integrating resilience, adaptability and transformability. *Ecology & Society, 15*(4), 299–305.

Gotts, N. M. (2007). Resilience, panarchy, and world-systems analysis. *Ecology & Society, 12*(1), 181–194.

Grundmann, P., Ehlers, M. H., & Uckert, G. (2011). Responses of agricultural bioenergy sectors in Brandenburg (Germany) to climate, economic and legal changes: An application of Holling's adaptive cycle. *Energy Policy, 48*, 118–129.

Gunderson, L. H., & Holling, C. S. (2002). *Panarchy: Understanding transformations in human and natural systems.* Washington, D.C: Island Press.

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology & Systematics, 4*(2), 1–23.

Holling, C. S. (2001). Understanding the complexity of economic, ecological, and social systems. *Ecosystems, 4*(5), 390–405.

Ingalls, M. L., & Stedman, R. C. (2016). The power problematic: Exploring the uncertain terrains of political ecology and the resilience framework. *Ecology & Society, 21*(1), 6.

Jiang, Z., Huete, A. R., Didan, K., & Miura, T. (2008). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Environment, 112*(10), 3833–3845.

Jing, W., Yang, Y., Yue, X., & Zhao, X. (2015). Mapping urban areas with Integration of DMSP/OLS nighttime light and MODIS data using machine learning techniques. *Remote Sensing, 7*(9), 12419–12439.

Lei, Y., Wang, J., Yue, Y., Zhou, H., & Yin, W. (2014). Rethinking the relationships of vulnerability, resilience, and adaptation from a disaster risk perspective. *Natural Hazards, 70*(1), 609–627.

Li, B. L. (2000). Why is the holistic approach becoming so important in landscape ecology? *Landscape & Urban Planning, 50*(1–3), 27–41.

Li, Y., Kappas, M., & Li, Y. (2017). Exploring the coastal urban resilience and transformation of coupled human-environment systems. *Journal of Cleaner Production,* 1–7.

Liu, Y., Peng, J., Zhang, T., & Zhao, M. (2015). Assessing landscape eco-risk associated with hilly construction land exploitation in the southwest of China: Trade-off and adaptation. *Ecological Indicators, 62*, 289–297.

Liu, Y., Wang, Y., Peng, J., Zhang, T., & Wei, H. (2015). Urban landscape ecological risk assessment based on the 3D framework of adaptive cycle. *Acta Geographica Sinica, 70*(7), 1052–1067 (in Chinese).

Ma, T., Zhou, C., Pei, T., Haynie, S., & Fan, J. (2012). Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: A comparative case study from China's cities. *Remote Sensing of Environment, 124*, 99–107.

Meerow, S., & Newell, J. P. (2017). Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit. *Landscape and Urban Planning, 159*, 62–75.

Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape & Urban Planning, 147*, 38–49.

Mo, W., Wang, Y., Zhang, Y., & Zhuang, D. (2017). Impacts of road network expansion on landscape ecological risk in a megacity, China: A case study of Beijing. *Science of The Total Environment, 574*, 1000–1011.

Müller, F., Bergmann, M., Dannowski, R., Dippner, J. W., Gnauck, A., Haase, P., et al. (2015). Assessing resilience in long-term ecological data sets. *Ecological Indicators, 65*, 10–43.

Olsson, P., Gunderson, L. H., Carpenter, S. R., & Ryan, P. (2006). Shooting the rapids: Navigating transitions to adaptive governance of social-ecological systems. *Ecology & Society, 11*(1), 441–473.

Paukert, C. P., Pitts, K. L., Whittier, J. B., & Olden, J. D. (2011). Development and assessment of a landscape-scale ecological threat index for the Lower Colorado River Basin. *Ecological Indicators, 11*(2), 304–310.

Peng, J., Dang, W., Liu, Y., Zong, M., & Hu, X. (2015). Review on landscape ecological risk assessment. *Acta Geographica Sinica, 70*, 664–677 (in Chinese).

Piet, G. J., Knights, A. M., Jongbloed, R. H., Tamis, J. E., Vries, P. D., & Robinson, L. A. (2017). Ecological risk assessments to guide decision-making: Methodology matters. *Environmental Science & Policy, 68*, 1–9.

Porter, L., & Davoudi, S. (2012). The politics of resilience for planning: A cautionary note. *Planning Theory & Practice, 13*(2), 329–333.

Rawluk, A., & Curtis, A. (2016). Reconciling contradictory narratives of landscape change using the adaptive cycle: A case study from southeastern Australia. *Ecology & Society, 21*(1), 17–27.

Resnick, M. D., & Taliaferro, L. A. (2011). Resilience. *Encyclopedia of Adolescence, 1*, 299–306.

Saura, S., & Torné, J. (2009). Conefor Sensinode 2.2: A software package for quantifying the importance of habitat patches for landscape connectivity. *Environmental Modelling & Software, 24*(1), 135–139.

Sharifi, A. (2016). A critical review of selected tools for assessing community resilience. *Ecological Indicators, 69*, 629–647.

Shiau, T. A., & Liu, J. S. (2013). Developing an indicator system for local governments to evaluate transport sustainability strategies. *Ecological Indicators, 34*(11), 361–371.

Singh, R., Werkhoven, K. V., & Wagener, T. (2014). Hydrological impacts of climate change in gauged and ungauged watersheds of the Olifants basin: A trading-space-for-time approach. *International Association of Scientific Hydrology Bulletin, 59*(1), 29–55.

Su, Y., Chen, X., Liao, J., Zhang, H., Wang, C., Ye, Y., et al. (2016). Modeling the optimal ecological security pattern for guiding the urban constructed land expansions. *Urban Forestry and Urban Greening, 19*, 35–46.

Tarazona, J. V. (2013). Use of new scientific developments in regulatory risk assessments: Challenges and opportunities. *Integrated Environmental Assessment & Management, 9*(3), e85–e91.

Teigão dos Santos, F., & Partidário, M. R. (2011). Spark: Strategic planning approach for resilience keeping. *European Planning Studies, 19*(8), 1517–1536.

USEPA (U.S. Environmental Protection Agency) (1998). Guidelines for ecological risk assessment. *Journal of Object Technology, 23*(4), 501–507.

Van Den Brink, P. J., Choung, C. B., Landis, W., Mayer-Pinto, M., Pettigrove, V., Scanes, P., et al. (2016). New approaches to the ecological risk assessment of multiple stressors. *Marine and Freshwater Research, 67*(4), 429–439.

Walker, B., Carpenter, S. R., Anderies, J. M., & Abel, N. (2002). Resilience management in social-ecological systems: A working hypothesis for a participatory approach. *Ecology & Society, 6*(1), 840–842.

Walker, B., Gunderson, L., Kinzig, A., & Folke, C. (2006). A handful of heuristics and some propositions for understanding resilience in social-ecological systems. *Ecology & Society, 11*(1), 709–723.

Walker, B., Holling, C. S., Carpenter, S. R., & Kinzig, A. P. (2004). Resilience, adaptability and transformability in social-ecological systems. *Ecology & Society, 9*(2), 3438–3447.

Wang, X. Q., & Gong, Y. B. (2010). The impact of an urban dry island on the summer heat wave and sultry weather in Beijing City. *Chinese Science Bulletin, 55*(16), 1657–1661.

Wischmeier, W. H., Johnson, C. B., & Cross, B. V. (1971). Soil erodibility monograph for farmland and construction sites. *Journal of Soil & Water Conservation, 26*(5), 189–193.

Xie, W., Huang, Q., He, C., & Zhao, X. (2018). Projecting the impacts of urban expansion on simultaneous losses of ecosystem services: A case study in Beijing, China. *Ecological Indicators, 84*, 183–193.

Zhou, W., Pickett, S. T. A., & Cadenasso, M. L. (2017). Shifting concepts of urban spatial heterogeneity and their implications for sustainability. *Landscape Ecology, 32*(1), 15–30.